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Leveraging Frontline Employees' Small Data and Firm-Level Big Data in Frontline Management: An Absorptive Capacity Perspective

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Abstract

The advent of new forms of data, modern technology, and advanced data analytics offer service providers both opportunities and risks. This article builds on the phenomenon of big data and offers an integrative conceptual framework that captures not only the benefits but also the costs of big data for managing the frontline employee (FLE)-customer interaction. Along the positive path, the framework explains how the "3Vs" of big data (volume, velocity, and variety) have the potential to improve service quality and reduce service costs by influencing big data value and organizational change at the firm and FLE levels. However, the 3Vs of big data also increase big data veracity, which casts doubt about the value of big data. The authors further propose that because of heterogeneity in big data absorptive capacities at the firm level, the costs of adopting big data in FLE management may outweigh the benefits. Finally, while FLEs can benefit from big data, extracting knowledge from such data does not discount knowledge derived from FLEs' small data. Rather, combining and integrating the firm's big data with FLEs' small data are crucial to absorbing and applying big data knowledge. An agenda for future research concludes.

Keywords

big data, big data absorptive capacity, frontline management, small data

> In our experience, many companies spend 90 percent of their investment on building models and only 10 percent on frontline usage, when, in fact, closer to half of the analytics investment should go to the front lines.
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> Brown, Court, and Willmott (2013)
>
> . . . At a sales call center, staff members failed to use a product-recommendation engine because they didn't know how the tool formulated the recommendations and because it was not user friendly. Once the tool was updated to explain why the recommendations were being made and the interface was improved, adoption increased dramatically. (p. 56)
>
> Court (2015)

Big data radically extends opportunities for firms and their frontline employees (FLEs) to go beyond transactional data to significantly improve frontline effectiveness and efficiency. For example, using sophisticated analytics infrastructure, the Oversea-Chinese Banking Corporation experienced a 45% increase in overall conversion rates and a 60% increase in cross-sales (IBM 2013). Similarly, AT&T collects 30 billion data points per hour to measure network quality, which it turns into insights to improve customer experience (King 2014). With success stories like these, the big data market has been growing at a fast pace, projected by International Data Corporation to reach US$187 billion in 2019, the majority of which are in services marketing.

While much has been written about the opportunities big data brings, the return on investment (ROI) of big data has not been thoroughly assessed (Wamba et al. 2015). A survey of more than 400 Gartner research circle members in 2015 indicated that 75% of these companies were investing or planning to invest in big data in the next 2 years, but about 40% of companies did not know whether their ROI would be positive or negative (Gartner 2015). Furthermore, as the opening quotes suggest, most firms that invest in big data do not fully realize the critical role of FLEs in big data marketing. Therefore, there

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is a need for a systematic account of (1) both the benefits and the costs of big data, (2) how firms can better leverage big data in frontline management, and (3) when and how FLEs' small data might be supplemented by and complement the firm's big data.

To address these issues, we draw from the literature on absorptive capacity (Zahra and George 2002) and knowledge creation (Nonaka 1994) to propose a conceptual framework that follows the big data → information → new knowledge → knowledge application chain, while accounting for (1) the moderating effect of the firm's big data absorptive capacity and (2) the interplay between the firm's big data and FLEs' small data. Specifically, our framework captures the conversion of big data availability (i.e., data) to big data value (i.e., information), which induces organizational change (i.e., new knowledge) that drives frontline outcomes (i.e., knowledge application). "Big data availability" refers to the 3V components (McAfee and Brynjolfsson 2012) of big data—namely, volume (i.e., the massive amount of data), velocity (i.e., the speed of data), and variety (i.e., difference sources of data). "Small data" refers to FLEs' data collected through their interactions and relationships with customers. We define "big data absorptive capacity" as routines by which a firm acquires, assimilates, transforms, and applies big data knowledge to create a dynamic marketing capability. This absorptive capacity is driven by the capability of combining and integrating big data and small data knowledge at both the firm and FLE levels.

The insights of the framework are threefold. First, it underscores a largely ignored fact that big data has both benefits and costs. Specifically, while big data availability enhances big data completeness, it also raises big data veracity, or inconsistency, which deters firms and FLEs from using it.[1] By delineating these effects, we provide useful insights into the positive and negative underlying processes of how firms and their FLEs convert big data into frontline outcomes. Second, the framework reveals the role of the firm's big data absorptive capacity in altering the balance between the positive and the negative impact of big data availability on frontline outcomes. Third, our comparison of FLEs' small data and the firm's big data provides insight into FLEs' role in building big data absorptive capacity, primarily by combining and integrating their small data knowledge with the firm's big data knowledge.

This article proceeds as follows: We first introduce our absorptive capacity–inspired conceptual framework that guides our examination of benefits and costs of big data in frontline management. For each key construct, we also provide the background literature. Next, we present research propositions on their relationships in the model. Then, we discuss the relationship between FLEs' small data and the firm's big data absorptive capacity. We conclude with an agenda and directions for future research.

Background Literature and Conceptual Framework

We depict our conceptual framework in Figure 1. Four key themes are embedded in this framework. First, the framework focuses on both the firm and its FLEs (we briefly explain customers' role in big data marketing in the Discussion section).[2] Second, viewed from the left to the right, our framework has two main effects components that follow the data → information → new knowledge → knowledge application chain. In our framework, knowledge refers to a set of expectations held by the agents at various levels (e.g., the firm and FLEs) and is modified by the arrival of information extracted from data, big or small (e.g., Boisot and Canals 2004). The first main effects component captures the conversion of big data availability to big data value in the form of useful, actionable information about customers, competition, and the market. In this article, we focus on an important big data value, namely, actionable customer insights. The second main effects component reflects the conversion of big data value to knowledge that can be applied in frontline activities. Horizontally, we depict these two components as two gray boxes at the bottom of Figure 1. Third, these relationships are subject to the firm's absorptive capacity, which includes its acquisition, assimilation, transformation, and application capacities. Due to these contingencies, the balance between the benefits and the costs of big data marketing, or ROI in big data, can be altered. Fourth, the firm's and FLEs' combinative and integrative capabilities contribute significantly to the development of the firm's big data absorptive capacity. Vertically, we depict these last two themes (i.e., using big data absorptive capacity to leverage big data and building big data absorptive capacity) as two gray boxes on the left margin.

Big Data–Related Constructs of the Framework

Big data volume. The world created 1 zettabytes of data in 2010 and is forecast to generate 40 zettabytes by 2020 (Villars, Olofson, and Eastwood 2011). IBM recently estimated that 2.3 trillion gigabytes of data are created each day (www.ibmbigdatahub.com). Big data volume refers to these massive amounts of data that allow firms to go beyond historical data and outside the focal customer touch points (e.g., stores and service stations) to achieve a more comprehensive view of the customer. Three often-used methods to generate big data in the services marketing context include passive learning, comprehensive customer tracking, and business data augmentation with nonbusiness data. Passive learning involves gathering customers' data *outside* their actual interactions with FLEs (Montgomery and Srinivasan 2002). For example, American Apparel uses a combination of security cameras, cell phone signals, and Wi-Fi to track customers within the store, providing insights into customer visiting patterns and movement behaviors (Brynjolfsson, Hu, and Rahman 2013). In comprehensive customer tracking, service providers track customers *outside* their physical location. For example, Target uses "social sentiment data" collected from various social networks to quickly uncover how customers feel about their design collaborations (Thau 2014). Finally, service firms can also rely on data *not* connected with the customer or service provider. For example, a Russian retailer gathered data on weather

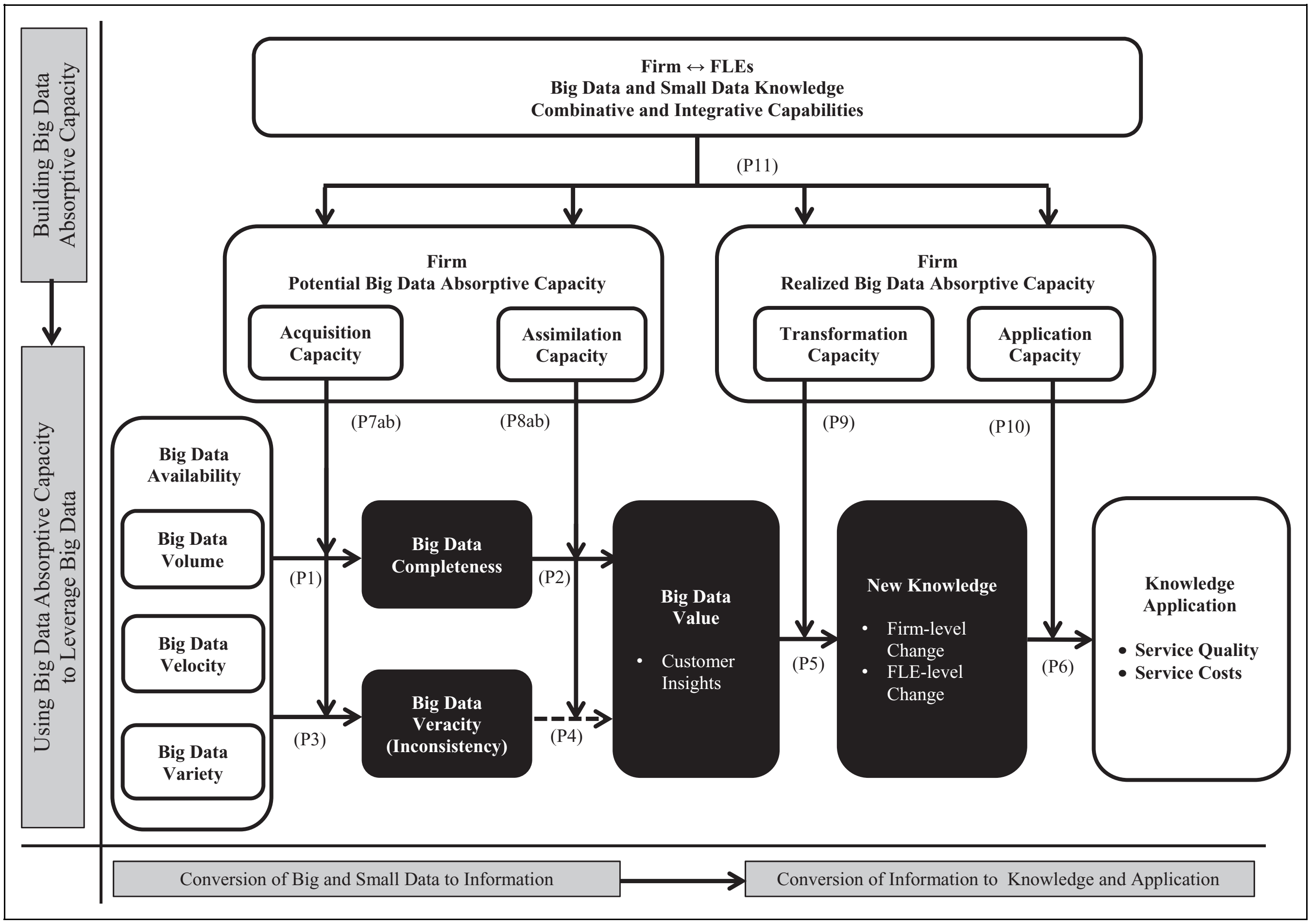

Figure 1. Conceptual framework. The dotted line represents a negative relationship. The gray boxes allow for a bird's-eye view of the framework.

conditions because it found that book sales increase as the weather turns colder (Marr 2015).

Big Data velocity. The speed at which data are generated represents big data velocity. For example, Wal-Mart handles more than one million customer transactions every hour, which it then imports into its massive databases of more than 2.5 petabytes (Wikibon 2012). With more than 175 million tweets every day and 100 tetrabytes of data uploaded daily to Facebook (Wikibon 2012), unstructured data can quickly overtake structured data.

Big Data variety. In addition to traditional forms of data such as purchase behavior, service firms can collect unstructured data such as Tweets, Instagram pictures, Facebook posts, and GPS coordinates across various platforms. Big data *variety* refers to different types of data sources. Firms can also gather data on customer sentiment, location, and online and off-line transactions, across various channels (e.g., Brynjolfsson, Hu, and Rahman 2013).

Big Data completeness. Drawing from research on data quality (e.g., Brohman et al. 2003), we define big data completeness as the extent to which big data is of sufficient breadth and depth for the relevant frontline tasks. Big data completeness enhances a firm's certainty about customer behavior in the past (e.g., through big data on past transactions), the current (e.g., by analyzing big data fused from a variety of sources), and the future (e.g., through predictive models using big data and through recommendation systems).

Big Data veracity. Despite its potential benefits for frontline management, big data can be costly in that it can be messy, leading to confusion. Following Walker (2012), we define big data veracity as the extent of consistency, accuracy, and usefulness of big data for functional use by a frontline manager or an FLE. Unlike the big data literature, which considers veracity one of the characteristics of big data, here we treat big data veracity as an endogenous variable.

Big Data value. Although academic research on the business value of big data is still scarce (Wamba et al. 2015), there is some evidence of the positive impact of big data value if it is properly extracted. For example, companies in the top third of their industry in the use of data-driven decision-making were, on average, 5% more productive and 6% more profitable than their competitors (McAfee and Brynjolfsson 2012). Conceptually, the mediating role of big data value is consistent with prior research on the use of market research information, which suggests that the actionability of market research information, which corresponds to big data value in our context, is one of the key factors that link market research and the extent of the actual use of research information (Moorman, Zaltman, and Deshpandé 1992). Big data value refers to actionable and economically worthy insights (Wamba et al. 2015).[3] Economically worthy information means that the benefits a firm expects to gain from the insights must exceed their costs to deserve further investment.

Although big data provides insights into various factors, such as the competition or the market as a whole (e.g., Liebowitz 2013), in this article, we focus on customer insights. The two most important customer insights from big data are (1) identification of a customer along with his or her preferences and habits and (2) his or her situational and emotional state. The lack of instant information about individual customers has been a significant problem for most service firms for a long time. In 2014, only 3% of North American retailers were able to identify customers walking into their stores (Smith 2014). Besides, the introduction of "mass services" (i.e., few employees, many customers) prevents recognizing individual customers and maintaining relationships with them (Carden 2011). Online services have been able to customize their offers through cookies and other techniques that enable the immediate recognition of a customer's identity, but off-line services have suffered from the lack of such ability, an issue that can now be overcome with new technologies. Another customer insight is the customer's emotional state, which can strongly influence customer's decision-making (Hennig-Thurau et al. 2006). Modern facial coding technologies can "read" a customer's emotional state in real time from his or her muscular microexpressions, and service firms have begun testing the use of emotion-detection software combined with security cameras (e.g., Dwoskin and Rusli 2015).

FLEs' Small Data

The firm and its FLEs as "knowledge agents" are not necessarily exposed to the same types of data. Compared with big data, FLEs' data are at the other end of the spectrum in terms of the 3Vs: volume (e.g., much smaller), velocity (e.g., generated slowly as the service encounter unfolds or through a relationship with a customer), and variety (e.g., generally from customers as a single source). We refer to these data as small data. It should be noted that even if the firm and its FLEs are exposed to the same data, the two levels may rely on very different absorptive capacity to extract information from them.

FLEs collect small data, extract information from it, and accumulate knowledge through their direct interactions and relationships with customers. As boundary spanners, FLEs can gather unique and context-specific data and knowledge about customer needs, problems in service delivery, ways to improve service quality, and customer sentiment and preferences (Santos-Vijande, López-Sánchez, and Rudd 2016; Ye, Marinova, and Singh 2012).

As FLEs' small data is not identical to the firm's big data, the information and knowledge extracted at the two levels also differ in at least two ways. First, FLEs' information and knowledge tend to be more tacit, local (e.g., location specific, customer specific), and unarticulated, whereas firm-level information and knowledge are more explicit, global (e.g., across locations, across customers, or segments), codified, and well articulated. Second, FLEs' information and knowledge about the customer are interpersonal, real time, emotional, and intuition based (e.g., Crossan, Lane, and White 1999), whereas much of firm-level big data about the customer is broad, mostly historical, lacking of emotions, and behavior based.

Data Absorptive Capacity: Big Data Versus Small Data

Cohen and Levinthal (1990, p. 128) define absorptive capacity as "the ability of a firm to recognize the value of new, external information, assimilate it, and apply it to commercial ends." Recent research has redefined absorptive capacity as organizational routines by which a firm acquires, assimilates, transforms, and applies knowledge to create dynamic capability (Zahra and George 2002). As mentioned in the Introduction section, we draw from this literature to define a firm's big data absorptive capacity as organizational routines by which the firm acquires, assimilates, transforms, and applies big data knowledge to create a dynamic marketing capability. Similarly, FLEs' small data absorptive capacity refers to FLEs' routines by which FLEs acquire, assimilate, transform, and apply small data knowledge in frontline activities.

Dimensions of data absorptive capacity. Research by Zahra and George (2002) delineates two key dimensions of absorptive capacities: (1) potential absorptive capacities, which include knowledge acquisition and assimilation and (2) realized absorptive capacities, which include knowledge transformation and application. Consistent with this perspective, we propose that data absorptive capacity also consists of potential and realized data absorptive capacity. These capacities are not necessarily positively correlated. The *potential* capacity component of absorptive capacity includes data acquisition and assimilation, while the *realized* capacity component of absorptive capacity includes data transformation and application.

In our context, we define *acquisition capacity* as routines that "knowledge agents" (the firm or FLEs) use to identify and acquire data (big data and small data, respectively) critical to their operations. *Assimilation capacity* refers to routines and processes that allow agents to analyze, process, interpret, and understand the information derived from the acquired data. *Transformation capacity* refers to the agents' capacity to develop and refine the routines that facilitate combining existing knowledge and insights from the assimilated information to create new knowledge. Finally, we define *application capacity* as routines that allow the agents to refine, extend, and leverage existing competences or to create new ones by incorporating transformed knowledge extracted from data into their frontline activities.

Comparing big data and small data absorptive capacity. Although absorptive capacity has primarily been applied in the R&D context and at the firm level, studies have called for further research that examines the construct in other areas of knowledge and at other levels of analyses, such as the individual level (e.g., Lane, Koka, and Pathak 2006). While a firm's absorptive capacity is grounded in its employees (Cohen and Levinthal 1990; Lewin, Massini, and Peeters 2011), there are significant differences between the firm's big data absorptive capacity and FLEs' small data absorptive capacity.

First, while a firm makes the decision to collect big data based on prior investment and current needs, FLEs acquire small data because of intrinsic drivers (e.g., an individual need to pay attention to small details to pamper customers) as well as extrinsic motivation (e.g., firm-provided incentives). Second, firms analyze big data primarily through logical deduction, with quantitative tools. In contrast, FLEs make sense of their small data primarily through practical experience, with an emphasis on qualitative cues. While firms can outsource some of their assimilation capacity, FLEs can adopt a similar strategy by learning vicariously from peers. Third, both firms and FLEs share some similarities in terms of resistance to change. At both levels, transformation capacity is not automatic. Similar to firms' organizational defense (Argyris 1985), FLEs may trust their own tacit knowledge accumulated through personal experience more than explicit and tacit knowledge imposed by other peers or from the top-down. Tacit knowledge refers to "work-related, practical know-how that typically is acquired informally as a result of on-the-job experience, as opposed to formal instruction" (Wagner et al. 1999, p. 157). Another important aspect of transformation capacity is knowledge sharing. In this regard, even when the firm imposes informal control mechanisms, such as a knowledge-sharing culture and norms, to foster knowledge sharing, FLEs might view sharing their own tacit knowledge as threatening. This is because tacit knowledge might help an FLE to achieve better performance than other FLEs. Finally, while there is generally a time lapse between the acquisition and the application of big data knowledge at the firm level (i.e., latency) and a high level of standardization, FLEs' application of data, whether big or small, is primarily on the fly and requires some adaptation.

Combinative and Integrative Capabilities

Absorptive capacity results from the capabilities of engaging in knowledge creation processes (Van den Bosch, Volberda, and De Boer 1999). Nonaka (1994) suggests four knowledge creation processes: socialization, combination, externalization, and internalization. Socialization (from tacit to tacit) involves passing on tacit knowledge through shared experience, observation, imitation, and practice. Combination (from explicit to explicit) involves integrating explicit knowledge into a formal knowledge system, through rules, procedures, and instructions. Externalization (from tacit to explicit) represents the process of articulating tacit knowledge into explicit concepts. Finally, internalization (from explicit to tacit) refers to embodying explicit knowledge into tacit knowledge through learning by doing.

Firms and FLEs differ in their capabilities of engaging in these four knowledge creation processes. Figure 1 proposes combinative and integrative capabilities as two key antecedents to absorptive capacity. Combinative capabilities (see Van den Bosch, Volberda, and De Boer 1999) refer to the firm's and FLEs' ability to share explicit and tacit knowledge, either through communities of practice or through socialization (Nonaka 1994). Much less attention has been given to integrative capabilities, which we define as the firm's and FLEs' ability to either facilitate or directly engage in (1) externalization of knowledge from FLEs' small data to complement the firm's big data and (2) internalization of knowledge from the firm's big data to complement FLEs' small data.

From Big Data Availability to Big Data Value

In this section, we focus on the first main effects component in our conceptual framework. Specifically, we present propositions that are related to the positive and negative relationships between big data availability and big data value.

The Positive Path From Big Data Availability to Big Data Value

From Big Data availability to Big Data completeness. Big data availability enhances big data completeness in several ways. First, the large volume of big data allows firms to impute missing values in the data. Second, the velocity or speed with which the data are generated makes it possible to observe sequences of customer behavior that would not have been possible otherwise. This observation allows firms to better understand customer behavioral patterns and dynamics over time. Third, the variety of data sources makes it possible to compare the data and even fuse the data together to create a more complete data set (e.g., Feit et al. 2013). This is important in the omnichannel context in which customers engage with the firm in several ways, sometimes bypassing the front line.

> **Proposition 1:** All other things being equal, big data availability is positively related to big data completeness.

From Big Data completeness to Big Data value. We propose the following three ways that big data completeness can create value for firms: (1) real-time decisions, (2) waste elimination, and (3) improved decision-making. First, by making information transparent and readily available, big data enables real-time decision-making and, in turn, frequent resource reallocation. Instead of making decisions for the near future and waiting for outcomes to make adjustments, big data allows firms to interact with their customers on a continuous basis and make real-time adjustments to their offerings to offer customer-specific and situational personalization (Rust and Lemon 2001). Thus, big data allows firms to move from low-frequency forecasting to high-frequency nowcasting (Manyika et al. 2011; Saboo, Kumar, and Park 2016). Second, tracking and collecting information on different aspects of organizational structure and processes gives managers a richer view of the firm and its customers. They can now accurately track everything from inventory utilization to employee engagement and advance the economic mission of the firm by eliminating waste and improving quality. For example, firms can analyze different attributes about their FLEs and their interactions with customers and other team members to determine the interventions necessary to improve FLE productivity. Third, the availability of the right information at the right analytical level can substantially improve managerial decision-making. Instead of relying on hunches, managers can use rich data to develop finer customer segmentation and better alignment of services with customer preferences. Therefore, we propose the following:

> **Proposition 2:** All other things being equal, big data completeness enhances big data value.

The Negative Path From Big Data Availability to Big Data Value

From Big Data availability to Big Data veracity. As the volume, velocity, and variety of data flowing into an organization increase, more knowledge about internal and back-end operations is required to verify data accuracy. Not all firms are able to cope with the data verification process because big data verification requires large investment in hardware, software, time, and personnel (Rizzatti 2014). Firms that are "born through analytics" such as Amazon or Facebook are better able at verification (Court 2015). Unable to verify the accuracy of all their data, many firms employ "sampling" procedures and use only a small subsample of information for decision-making. Such sampling procedures circumvent the problem of data verification but increase the chances of data inaccuracy (Delgado 2015). Therefore, we propose:

> **Proposition 3:** All other things being equal, big data availability increases big data veracity.

From Big Data veracity to Big Data value. Low-quality data waste storage can be difficult to process and, worse, provide misleading results. The old dictum of "garbage in, garbage out" is especially true here, as the messiness of big data can make verifying the trustworthiness or usefulness of the data difficult. We posit that big data veracity increases a firm's coordinating costs or the expenses incurred from managing interdependent functional activities across the internal front line and customers (Ray, Wu, and Konana 2009). Such coordination costs might require additional front-end staff, as the frontline organization attempts to harness the power of big data throughout the organization, which in turn increases day-to-day coordination costs. High levels of big data veracity also increase day-to-day adjustments in the frontline organization, slowing down decision-making, increasing the complexity of new operations, and creating self-doubt in the frontline management team about using big data in decision-making. Thus, we propose the following:

> **Proposition 4:** All other things being equal, big data veracity impairs big data value.

From Big Data Value to Frontline Outcomes

In this section, we focus on the second main effects component of our conceptual framework. Specifically, we discuss firm- and FLE-level change as mediators of the impact of big data value on service quality and costs.

Firm-Level Change

As suggested in the opening quotes, although transmitting big data value to FLEs is critical, the effectiveness of doing so ultimately depends on the FLEs' *usage* of the information. Such usage, however, is far from certain because FLEs are not simply "organizational soldiers," and their workplace behavior is also driven by self-interest motives (e.g., De Dreu and Nauta 2009). Thus, we argue that effective organization-level change is required to accompany the provision of big data value to FLEs to generate positive service outcomes. In this regard, the human utility framework (Becker 1976) suggests that organization-level change must produce conditions that either increase FLEs' perceived benefits of applying big data value or reduce the costs thereof. Such conditions require concerted actions that affect several organizational dimensions, including culture, technology, and processes. We discuss these dimensions next.

Cultural change. Big data value induces cultural change that puts stronger emphasis on utilization of the insights extracted from big data (Davenport 2014). Big data applications are likely to flourish in an organizational culture that perceives the use of big data value as a positive, integral element of the service delivery process and puts emphasis on big data–related metrics (Davenport 2014; Sathi 2014).

Technological change. Applications of big data value involve the need to adopt new technologies that complement FLEs' traditional service provision (e.g., the use of wearable technologies in service encounters) or even substitute the FLEs (e.g., check-in robots at the Japanese Henn-na Hotel; Wong 2015).

Process change. Finally, service firms that appreciate the value in big data are likely to implement processes that facilitate their FLEs' application of big data value in service design, innovation, and delivery. Well-designed processes should support the flow of data and enable the FLE to embed the customer data organically in his or her interactions with customers. Service firms, such as PNC Bank (Davenport 2014), have begun adopting well-structured and semiautomatic processes for customer service so that call center agents (no direct customer contact, low customer proximity) and customer service employees (high customer proximity) can rely on these new models to personalize offers across all customer contact points and channels.

FLE-Level Change

On the FLE level, big data value requires FLEs to undergo training to acquire a new skill set, including basic analytical skills to digest and use big data insights, service technology savviness, and social media proficiency. Training sessions on big data–related software and hardware can better acquaint FLEs with big data technology, lowering their perceived costs of use. FLEs do not need to be data scientists, but they must be creative implementers. As the traditional FLE role is replaced or complemented by new technologies, new roles emerge that require FLEs not only to overcome self-insecurity but also to possess a higher level of coordination skills to be the irreplaceable link among the firm, the technology, and the customers. Furthermore, big data value leads to changes in incentives or, more broadly, the informal and formal control systems. The traditional incentivization scheme needs to evolve to account for applying big data value. It can include monetary incentives for employees (e.g., a bonus for the frequency of customized smart data usage) and various nonmonetary rewards (e.g., preferred working schedules).

Several firms that adopt big data have begun giving FLEs the opportunity to use real-time big data information at the "moment of truth" to increase the level of service quality perceived by the customer. The provision of such information can be executed verbally or visually. For example, FLEs can be briefed by a computer about a customer entering the store through text-to-speech tools (similar to a television journalist). Information provision through visual aids, such as an installed monitor or a wearable device, is clearly less limited.[4] Compared to traditional installed monitors, wearable technology enables the service firm to provide FLEs with customer insights and product-related information regardless of their spatial location in the service scape. This discussion of firm- and FLE-level change induced by big data value leads to the following formal proposition:

> **Proposition 5:** All other things being equal, big data value induces organizational change in various dimensions, at both the firm level and the individual FLE level. There is an organic, dynamic relationship between the two levels of change.

The Consequences of Organizational Change

In this section, we delve deeper into service costs and customers' service quality perceptions as two key outcome metrics for service providers. Service quality is indicative of the firm and FLEs' effectiveness because service quality is positively related to customers' future spending, willingness to pay, and referrals (e.g., Parasuraman, Zeithaml, and Berry 1988; Zeithaml, Berry, and Parasuraman 1996), while service costs reflect frontline efficiency. Organizational change enhances service quality and reduces service costs because such change makes it possible to engage in more personalization and new technologies.

The potential impact of Big Data value through personalization. Real-time identification of individual customers through beacons and similar technology can help improve several dimensions of service quality. Identification can boost customer perceptions of FLEs' empathy levels, as the FLEs now have access to background information about past shopping behaviors and experiences, including service failures. Such information allows FLEs to address the customer in a personalized way, starting from a personal greeting to acknowledging previous service episodes and even offering regret (and maybe even compensation) for earlier service failures.[5] Personalization through technologies that transform big data value into frontline actions can also increase customers' perceptions of responsiveness. Knowing the preferences and shopping background of customers should enable FLEs to provide quicker, better fitted responses. Furthermore, such personalized treatment should inspire customer confidence and trust, positively affecting the assurance dimension of service quality.

The potential impact of Big Data value through new technology. The use of new technologies that are based on big data value potentially enhances how customers perceive the service scape. When these big data technologies are integrated with other tangible elements such as furniture and artifacts (Bitner 1992) at the customer interface, customers will perceive the service scape as more modern and "digital ready." New technology can even substitute FLEs altogether, potentially reducing service costs. This discussion leads to the following:

> **Proposition 6:** All other things being equal, organizational change at the firm and FLE levels enhances service quality and reduces service costs.

Moderating Effects of Big Data Absorptive Capacity

Our conceptual model proposes that the four dimensions of the firm's big data absorptive capacity moderate the transformation from big data availability to frontline outcomes. Because these dimensions are not necessarily correlated and differentially moderate different phases of this transformation, they help explain the disconnection between levels of investment in big data acquisition and returns on such investment. For example, many telecommunications companies collect massive amounts of data from their smartphone and tablet subscribers. However, T-Mobile was one of the few companies to reduce

Table 1. Dimensions of the Firm's Big Data Absorptive Capacity.

	Potential Absorptive Capacity		Realized Absorptive Capacity	
	Acquisition Capacity	Assimilation Capacity	Transformation Capacity	Application Capacity
Components	• Prior investments in big data • Intensity in big data acquisition (e.g., current investment) • Speed of big data acquisition • Direction or focus in big data acquisition	• An understanding of big data value • An appreciation of big data veracity	• Internalization of new knowledge extracted from big data • Conversion of big data to actionable insights	• Serendipitous use • Systematic implementation • Conversion of big data to economically worthy applications
Absorptive Routines	• Identifying and recognizing new knowledge that can be extracted from big data • Facilitating variation: Processes and norms that facilitate exploration of big data • Investing in computational capability and data security	• Fusion of online and off-line data • Fusion of data of various granularities (e.g., individual vs. aggregate level) • Facilitating collaboration with outside organization for data analytics	• Integrating new insights from big data with existing firm knowledge • Sharing and transferring knowledge derived from big data across the organization • Firm's structure and processes that facilitate organization change	• Internal selection regimes: Processes that firms use to select various big data frontline applications and determine how to allocate resources among them • Reflecting, updating, and replicating successful use of big data in services marketing • Ability to legally protect big data–based innovation and customer solutions

customer churn by 50% by staying on top of usage patterns, geographical usage trends, customer purchases by location, and, most important, customer lifetime value (Oaks 2015). In Table 1, we summarize the key components of big data absorptive capacity to make this construct more concrete.

Moderating Effect of Big Data Acquisition Capacity

The absorptive capacity literature (Zahra and George 2002) suggests that the components of big data acquisition capacity include prior investments in big data, the intensity of current effort in big data, the speed of acquiring big data, and the direction or focus in big data acquisition. Two important internal absorptive routines that influence these components include (1) the identification and recognition of big data relevant to the firm's objectives, which is one of the key challenges in big data implementation (Marr 2016) and (2) organizational norms that facilitate variation (e.g., Lewin, Massini, and Peeters 2011). The first routine ensures that the investment in big data is focused, while the second routine allows for exploration of new ideas that can be extracted from big data to improve frontline operations.

Big data acquisition capacity captures the intensity, speed, and direction of a firm's efforts to identify and gather information and therefore should improve the breadth, the depth, and also the business relevance of the data. However, because a firm that is capable of collecting massive amount of big data also runs the risk of information overload, acquisition capacity significantly increases the messiness of the data. Therefore, we propose the following:

> **Proposition 7:** Big data acquisition capacity (a) enhances the positive effect of big data availability on big data completeness and (b) exacerbates the positive effect of big data availability on big data veracity.

Moderating Effect of Big Data Assimilation Capacity

The key component of assimilation capacity is to develop an understanding of big data and an appreciation of big data veracity. Such a process sometimes involves borrowing skills from other companies. For example, to enhance the customer experience, a team of analysts at Desjardins, a large Canadian financial cooperative, expanded the network of experts to include people with best practice knowledge outside the financial services industry (Harrysson, Metayer, and Sarrazin 2012).

Assimilation capacity serves as a sieve that companies use to make sense of big data and transform big data into valuable, actionable insights (or big data value). Assimilation capacity, such as excellent data analytics and data fusion from various sources, should also allow these firms to overcome the noise from data veracity. Indeed, research shows that firms deploying analytics perform better than those that do not employ such practices, as such firms are better prepared to understand what customers want and to react to changes in customer and environmental trends (Germann, Lilien, and Rangaswamy 2013). In the frontline context, we expect firms with strong analytical capabilities to be able to solve fundamental customer-related issues, such as understanding customers' diverse needs (i.e., manage customer heterogeneity), understanding diverse customer dynamics (i.e., manage customer change), and responding to competitors' efforts (i.e., manage competitive dynamics). Taken together, this discussion leads to the following proposition:

> **Proposition 8:** Big data assimilation capacity (a) enhances the positive effect of big data completeness on big data value and (b) buffers the positive effect of big data veracity on big data value.

Moderating Effects of Big Data Transformation Capacity

While big data assimilation capacity is focused on how the firm makes sense of big data to extract useful information, big data transformation capacity is focused on how the firm transforms and integrates the extracted information into the firm's existing knowledge. We argue that while big data value increases the need for the firm and its FLEs to undergo change, the firm's big data transformation capacity not only facilitates such change process but also makes it less disruptive. Two key components of transformation are internalization and conversion, which occur when firms add new insights, delete obsolete knowledge, or interpret the same knowledge in a different light (Zahra and George 2002). The internal absorptive routines that underlie this capacity include routines that facilitate the integration of big data insights with the firm's existing knowledge about frontline issues, the sharing and transferring of big data insights across the organization, and the identification of the firm's shortcomings in its existing structure and frontline processes. Furthermore, a firm that possesses strong transformation capacity is better able to merge new insights derived from big data with its existing knowledge such that the change process allows for some levels of continuation and is less disruptive to organizational members. For example, firms with strong transformation capacity are likely to introduce management initiatives that integrate big data value into the company's strategies and to allocate sufficient resources to its implementation and execution. Furthermore, top managers in these firms are responsive to the multifarious challenges that digital marketing brings, thereby affecting the cultural transformation process similar to the way top management's commitment to service quality affects FLEs' performance (Babakus et al. 2003). Therefore, we propose:

> **Proposition 9:** Big data transformation capacity enhances the positive effect of big data value on organizational change at both the firm and the FLE levels.

Moderating Effect of Big Data Application Capacity

As this final step of application is focused on exploitation of knowledge and value appropriation rather than exploration of new ideas, a firm with strong big data application capacity has processes that allow it to select and prioritize various big data applications, to reflect and update big data application success, and to legally protect big data–based innovations and customer solutions. The logic of the enhancing moderating role of big data application capacity lies in the ability of firms that possess a strong application capacity to be highly creative and adaptive in applying new insights. Firms with a strong application capacity are also selective in their investment in applications, which further elevate the cost reduction effect of the change they go through after extracting big data insights. Therefore, we propose:

> **Proposition 10:** Big data application capacity enhances the service quality–enhancing effect of organizational change and the cost-reducing effect of organizational change.

The Role of Combinative and Integrative Capabilities

When Combinative and Integrative Capabilities Matter

Why do firms and FLEs need combinative and integrative capabilities to develop big data absorptive capacity? One reason is that firms and FLEs that have strong combinative and integrative capabilities leverage rather than being impeded by the differences between firm- and FLE-level data, information, and knowledge, which in turn enables the firm to develop stronger big data absorptive capacity. The top half of Figure 2 summarizes several contexts when FLEs' knowledge needs to be complemented by the firm's knowledge and vice versa. Specifically, when (1) customers transition from traditional customers to more sophisticated ones, (2) FLEs have less autonomy and the organization becomes more centralized, and (3) competitive intensity is strong, and the capabilities to complement big data with small data, and vice versa, will be strongly needed to drive better absorption of big data. While the organization structure determines FLEs' autonomy, customers' and competitors' access to big data calls for the combination and integration of big data and small data at both the firm and the FLE levels.

When the contexts exhibit characteristics listed on the left-hand side of Figure 2, the firm relies more on FLEs' tacit knowledge in its frontline activities, and therefore, FLEs' small data play a more important role than big data. In contrast, when the contexts have characteristics listed on the right-hand side, FLEs' small data and tacit knowledge are simply not enough to fulfill their responsibilities. In the latter case, the firm and its FLEs need to actively share tacit knowledge (i.e., socialization) and combine knowledge across organizational members (i.e., combination). These two processes are combinative in nature (e.g., Van den Bosch, Volberda, and De Boer 1999). More important, the firm's big data knowledge needs to be internalized by FLEs and fused with FLEs' tacit knowledge (i.e., internalization). The firm can also actively transform FLEs' small data and tacit knowledge into a more explicit form of

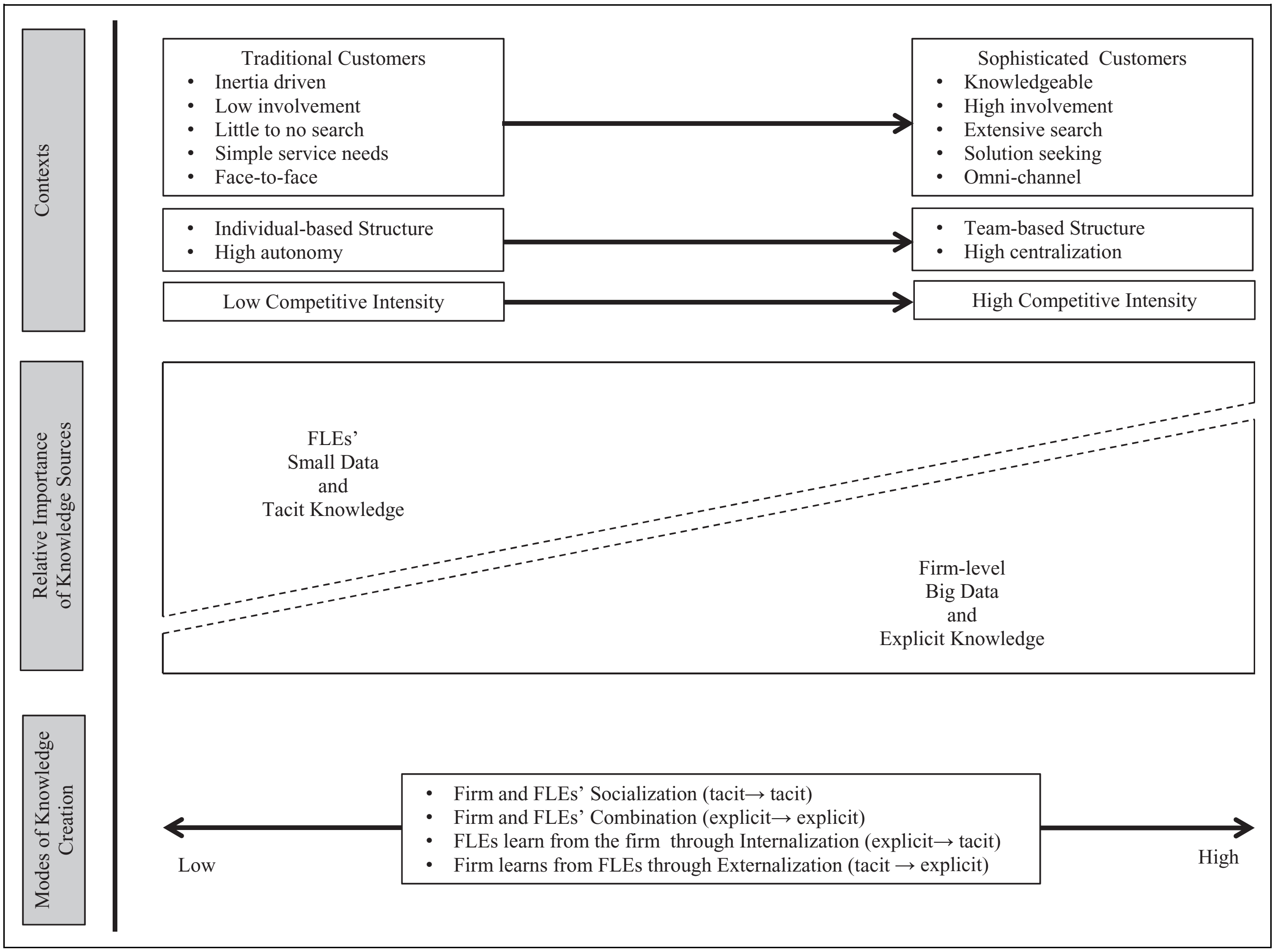

Figure 2. Contexts, relative importance of knowledge sources, and modes of knowledge creation processes.

knowledge that can be shared on a wider scale (i.e., externalization). These two processes are more integrative than the former two.

Combinative and Integrative Capabilities as Drivers of Big Data Absorptive Capacity

Knowledge creation processes are dynamic. In our context, combinative and integrative capabilities allow knowledge that is absorbed at one level (the firm or the FLE level, through big data or small data, respectively) to be combined and integrated with knowledge that is absorbed by the other level, thereby enhancing the other level's absorptive capacity in the subsequent time period. Based on this argument, we propose that combinative and integrative capabilities at both the firm and the FLE level contribute to the firm's big data absorptive capacity.

First, scattered data lying in silos, a disconnection between business and analytics, and a lack of clear objectives are major challenges of big data implementation (Capgemini 2015; Marr 2016). When the firm and its FLEs possess strong combinative and integrative capabilities, frequent and smooth knowledge creation processes allow the firm to overcome these challenges by being better at assessing its current knowledge and developing clearer objectives in its acquisition of big data. Second, big data assimilation presents several challenges. On the one hand, big data exists both online and off-line (Deighton and Johnson 2013). The fusion of data from various sources is challenging owing to different granularities of the data (e.g., aggregate data vs. individual-level data, identifiable vs. non-identifiable data). On the other hand, big data volume, velocity, and variety require unique analytical tools, skills, and information technology. When the firm and its FLEs are highly capable of combining and integrating big data with small data knowledge, the firm's capacity to discern valuable information from messy data is much improved.

Third, strong capabilities of combining and integrating the firm's big data with FLEs' small data enable the firm to improve its transformation capacity because those capabilities enable the firm to keep stock of knowledge at various levels within the organization and allow it and FLEs to identify opportunities for change. Finally, if FLEs resist internalizing

Table 2. Short-Term Research Agenda.

Paths	Specific Research Questions
P1, P2, P3, P4	**Theme 1: Firm's perspective of big data 3Vs and big data value and veracity**
	(1) How can firms collect and use data from face-to-face customer interactions without disrupting the customer experience or causing customer privacy concerns?
	(2) What specific data types (e.g., panel data, social media, brand communities) provide the greatest big data value and under what conditions (e.g., service type, firm characteristics)?
	(3) What are the specific firm-level factors that determine whether data will provide a positive (value) or negative (veracity) outcome for service firms?
	(4) What are the key differences between big data (e.g., data warehouse) as stocks and big data as flows (e.g., data streams)? How differently should firms treat these two types of data?
	Theme 2: FLEs; perspective of big data 3Vs and big data value and veracity
	(5) How do FLEs evaluate big data value?
	(6) How do firms incorporate FLEs' perspectives in analyzing big data?
	(7) What is the role of peer influence and/or group norms and managerial influence in determining big data value?
P5, P6	**Theme 3: Firm-level application of big data value**
	(8) What are firm- and industry-level moderators (e.g., high-touch specialty retailers versus mass-market retailers, employee-to-customer ratio) of the effects of big data value on frontline outcomes?
	(9) Identify avenues when big data can have maximum influence on firm value.
	(10) How much tolerance does firms' top management have about big data veracity?
	(11) When should firm desorb big data value to other firms to monetize its big data value?
	Theme 4: FLEs' application of big data value
	(12) What are the key determinants of FLE-perceived benefits and costs when it comes to using big data value?
	(13) How do FLEs respond to technology that substitutes or complements their service delivery? Does new technology impair FLEs' morale?
	(14) How much tolerance do FLEs have about big data veracity?
	Theme 5: Organizational control, organizational change, and big data
	(15) How effective are cultural controls versus rule-based controls over FLEs use big data value?
	(16) What are the stages of organizational change induced by big data?
	(17) What firms are better at managing organizational change induced by big data?What are the facilitators and inhibitors of the interplay between firm-level change and FLE-level change during big data application?
	(18) When do big data–triggered FLE changes have a stronger/weaker impact on customers' service quality perceptions and other services marketing outcomes?
P7, P8, P9, P10, P11	**Theme 6: The relationship between big data and small data**
	(19) Can too much tacit knowledge lead to FLEs' resistance to new insights from big data?
	(20) FLEs' small data can complement, impede, or substitute firm-level big data: what type of FLEs characteristics? Under what situations?
	(21) How do FLEs' combinative and integrative capabilities contribute to, strengthen, and/or weaken the effects of the firm's big data absorptive capacity?
	(22) How do business unit climates (e.g., service climate, selling climate, social norms) drive FLEs' engagement in evaluating big data value?
	Theme 7: Absorptive capacity
	(23) What are unique antecedents to potential versus realized big data absorptive capacity?
	(24) Under what conditions should firms outsource a specific big data capacity?
	(25) How do firms evaluate ROI in building absorptive capacity of big data and small data?
	(26) How does a firm's application capacity help reduce latency, or the time lag between the moment actionable insights are extracted and when applications actually take place?
	(27) What are FLEs' roles in data governance? How should firms organize the interface between data stewards and FLEs to effectively leverage FLEs' small data absorptive capacity?
	Theme 8: Customer acceptance of big data marketing
	(28) How should the usage of big data be disclosed to customers? How do firms utilize heterogeneity of customers' acceptance of big data marketing as a means of customer segmentation?
	(29) What are the effective ways to identify customers and gain their acceptance about being identified? What is the potential of beacons in this context?
	(30) How long does the effect of new service technology coolness and/or newness last?
	(31) What customer characteristics buffer the adverse effect of big data acquisition capacity on customer concerns about privacy?
	(32) How do customers react to "supersmart" hard- and software solutions that substitute "human" FLEs?

Note. Some research questions can be categorized in more than one box. FLE = frontline employee; ROI = return on investment.

the firm's big data knowledge, application of big data insights will not happen. Because big data transformation and application require the firm and its FLEs to complement and learn from each other (e.g., cross-level learning; Crossan, Lane, and White 1999), the firm's transformation and application capacity depends more on the firm's and FLEs' integrative capabilities than on combinative capabilities. More formally, we propose the following:

> **Proposition 11:** The firm's and FLEs' combinative and integrative capabilities drive the firm's big data absorptive capacity. However, integrative capabilities that involve internalization and externalization play a *more* important role in driving the firm's transformation and application capacity than combinative capabilities.

Discussion

In this conceptual article, we present a framework that systematically organizes the vast literature on big data. Multiple research themes emerge from our conceptual framework. We provide a list of specific questions that we find most pressing in this fairly new domain in Table 2. In the remainder of the article, we briefly discuss four issues that we have not covered in the previous sections: (1) deriving big data from FLE-customer interactions, (2) factors contributing to internalization and externalization, (3) customer variables relevant to big data marketing, and (4) measurement issues. These first two issues are managerially relevant because they inform managers of ways to creatively generate big data from service interactions and how to effectively strengthen absorptive capacity. The last two issues are relevant to future research.

Deriving Big Data From Frontline Employee-Customer Interactions

Thus far, we have discussed how FLEs' small data is complemented by and supplements firm-level big data, but we assume that these data sources are extracted independently. However, new technology has made it possible for service firms to derive big data from FLE-customer interactions. Such derivation depends on the service channel in which the FLE-customer interaction takes place because the technology of each channel provides a different potential for data recording and subsequent transformation into valuable information.

Service interactions via social media. The main challenge for deriving insights from this channel is to link a social media user's articulations with other kinds of company-owned information about this particular customer, which requires matching structurally different data sources via imperfect information, such as e-mail addresses and (user) names. Customer articulations on the firm's social media sites can be analyzed in multiple ways, such as using sentiment analytical procedures (to learn about the customer's emotional patterns and states), but topical interests and concerns (e.g., customer pain points) can also be extracted through machine learning and similar forms of artificial intelligence. By integrating such analyses on a large set of customers, the firm can learn from "similar" customers' preferences and articulations, which can be identified via matching and recommender algorithms.

Service interactions via telephone interactions. Services are often provided via call centers and helplines, whose analogue and real-time two-way nature makes the extraction of valuable information more complicated. Recordings (with customer permission) can be digitized and processed with content analysis software; the outcome of such technological transformation can then be applied to techniques similar to social media data, with information ranging from customers' emotions to customers' service-related preferences.

Face-to-face service interactions. Given its nontechnical, nonmediated, and highly dynamic character, this service channel is the most challenging when it comes to data recording and transformation. New technologies allow firms to extract additional information from these interactions, including the consumer's voice, facial reaction, and emotional change during the service interaction. This channel can also reveal additional information about the customer that might be useful in future service transactions, such as contextual information (e.g., Is the customer usually in a hurry when shopping? Is he or she alone or accompanied by others?).

Factors Contributing to Internalization and Externalization

As we mentioned earlier, internalization (i.e., embodying explicit knowledge into tacit knowledge through learning by doing) and externalization (i.e., articulating tacit knowledge into explicit concepts) represent integrative capabilities that drive the firm's big data absorptive capacity. In this section, we briefly review how firms can foster these capabilities.

Internalization. The firm's big data knowledge must be transformed into tacit knowledge by FLEs to be incorporated in customer interactions. Prior research suggests that FLEs' willingness to internalize big data knowledge depends on their goal orientation (e.g., learning orientation, performance orientation; see Elliot and Harackiewicz 1996) and basic personality, such as openness to change. Therefore, these are important traits to use in FLE selection. In addition to selection, firms can facilitate and motivate FLEs to internalize big data knowledge in several ways. First, as most FLEs are not familiar with analytics, using intuitive end-user interfaces that employ familiar technologies such as smartphones and tablets will reduce the amount of FLEs' training while increasing usage (Brown, Court, and McGuire 2014; Varon 2013). Second, the information available should relate to existing practices and strategies. For example, UPS incorporated role-based training when it rolled out new technology to its drivers to ensure that they understood not only the technology but also how decisions were being made by the system (Varon 2013). Unfortunately, many firms primarily focus on building the big data infrastructure and spend minimal time on frontline usage and adoption (Brown, Court, and Willmott 2013).

Externalization. Externalization of FLEs' information and knowledge has several challenges. First, FLEs' data on a specific interaction often remain at the individual level. Second, externalization depends on frontline managers who make the decision on whether to incorporate or ignore the data provided (Engen and Magnusson 2015). Third, FLEs may not be willing to share their tacit knowledge. The sales literature suggests that employees' upward mobility and job satisfaction play a critical role in motivating them to engage in information sharing. In addition, feedback from managers and trust further motivate information sharing because FLEs witness the customer information provided being used to support the business (e.g., Le Bon and Merunka 2006). For example, JetBlue uses a series of online polls, brainstorming events, and town halls to gather and collect information from customer-facing employees for use across the organization (Azzarello, Debruyne, and Mottura 2012). An organizational climate that fosters trusting relationships and a management commitment to incorporating new knowledge further encourages FLEs to share information (Bock et al. 2005). This approach is well implemented by J.C. Penney, which relies on data-driven decision-making, but the key component of its business strategy is to interact with and listen to FLEs to obtain information on customer needs to improve inventory management (Wahba 2016).

Customer Variables

Our viewpoint centers on the firm and FLEs. Further research could explore the role of customers by examining the effect of customer privacy concerns and customer acceptance of big data marketing on the relationships in our conceptual framework. *Customer privacy concerns* refer to the apprehension of (1) intrusion, (2) disclosure of private facts, (3) false public portrayals, and/or (4) inappropriate appropriation of information that customers expect to experience (McWhirter and Bible 1992). *Customer acceptance of* big data *marketing* refers to the extent to which customers are willing to engage in a firm's big data marketing. This engagement can take various forms, from information sharing (e.g., through an opt-in process) to providing useful inputs in cocreating products and services. A closely related construct is customer adoption of new technology and services. The literature on self-service technologies (Meuter et al. 2005), customer adoption of technology (Venkatesh, Thong, and Xu 2012), and technological savviness (e.g., Macdonald and Uncles 2007) informs several relevant variables to consider. The use of technology as a substitute for FLEs usually limits the response options, which might lead to customer frustration. In addition, today's technology prevents the provision of social benefits that might be essential for some customers (e.g., Hennig-Thurau, Gwinner, and Gremler 2003). To offer guidance for further research on these issues, we provide specific research questions on the role of customers in Table 2.

Measurement Issues

The challenge in investigating big data availability (i.e., the 3Vs) lies in the measurement issue. A useful approach is to develop an industry-specific benchmark because what is considered large in one industry might be negligible in another. This relativeness also depends on whether the firm's primary goal is to collect big data for its own use or for developing "desorptive capacity" (i.e., selling insights extracted from big data to other firms). For example, the volume measures should assess the total amount of data the firm collects relative to its competitors in its main industry. Velocity can be measured by perceptions of how quickly the firm can identify and capture data as they become available relative to the competition. The variety measure should capture the amount of data collected from transactional, in-store, or external sources, such as social media, also benchmarked against the competition.

No measurement scales exist to evaluate big data and small data absorptive capacity, combinative and integrative capabilities. Researchers interested in developing this measure can refer to the rich literature on absorptive capacity. However, even in this literature, a valid measure of individual absorptive capacity does not exist. Therefore, we urge researchers in this domain to take the first step to develop reliable measurements of the firm's big data absorptive capacity as well as FLEs' small data absorptive capacity. Measures of big data absorptive capacity can be developed by integrating the literature on absorptive capacity and prior work on customer information use (Jayachandran et al. 2005), data-driven decision-making (Brynjolfsson, Hitt, and Kim 2011), and market research use (Moorman, Zaltman, and Deshpandé 1992). We draw from the literature on absorptive capacity (Camisón and Forés 2010) to develop preliminary items to measure the four dimensions of firm-level big data absorptive capacity (see Table 3). These items provide directions for future scale development.

Conclusion

Our conceptual framework covers both the benefits and the costs of using big data in FLE service encounters. We propose that while big data completeness allows firms to derive the mean value of insights, big data veracity determines the error and trust in these insights. The notion of trust in big data value is central to big data utilization, as suggested by prior research in marketing information and market research use (e.g., Moorman, Zaltman, and Deshpandé 1992). Big Data insights do not guarantee improvement in service quality and reduction in service costs; rather, it is the change at both the organizational and the FLE levels that produces these positive outcomes. Finally, several contexts intensify the need for multilevel interplay

Table 3. A Sample of Measurement Items of Firm-Level Big Data Absorptive Capacity.

Dimensions	Sample Items (Scale Anchors: Strength of the Focal Firm Relative to the Competition)
Potential absorptive capacity: Acquisition	1. Capacity to capture relevant and up-to-date information on current and potential competitors 2. Degree of top management to continuously monitor the environment to discover new opportunities to be exploited proactively instead of waiting to see what happens 3. Frequency and importance of cooperation with big data institutions 4. Effectiveness in establishing programs oriented to the development of big data acquisition
Potential absorptive capacity: Assimilation	1. Ability to use employees' level of knowledge, experience, and competencies in the assimilation of new knowledge from big data 2. The firm ability to assimilate big data insights from the successful experiences of firms in the same industry 3. Attendance of big data training courses and conventions 4. Ability to develop knowledge management programs, guaranteeing the firm's capacity to understand and carefully analyze big data 5. Firm's competencies in big data analytics
Realized absorptive capacity: Transformation	1. Capacity of the firm to use information technologies to improve information flow and foster knowledge sharing among the firm's members 2. Firm's capacity to eliminate obsolete internal knowledge, thereby stimulating the search for alternative innovations and their adaptation 3. Capacity to adapt big data insights uncovered by other companies to the firm's particular needs 4. Degree to which firm allows all employees to voluntarily share useful big data to each other 5. Capability of coordinating and integrating all phases of the big data process and its interrelations with the functional tasks of engineering, production, and marketing
Realized absorptive capacity: Application	1. Firm's capacity to exploit new big data knowledge in frontline activities 2. Degree of application of big data insights to frontline processes prioritized in the firm's strategy 3. Capacity to put big data knowledge into products, services, and process patents 4. Ability to innovate to gain competitiveness by broadening the portfolio of new products, services, capabilities, and technology ideas, rather than responding to the requirements of demand or to competitive pressure

between the firm and its FLEs; extracting knowledge from big data does not discount the role of knowledge derived from FLEs' small data. In fact, without small data, big data may be more big costs than useful benefits. We hope that the insights from our framework will generate exciting research that helps managers effectively use big data in services marketing.

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Notes

1. In a recent survey, 27% of respondents were unsure of how much of their data were inaccurate (www.ibmbigdatahub.com).
2. A firm's acquisition and repository of big data and customers' contributions (e.g., social media postings) are important sources of big data availability but not the only ones. Big Data availability can exist even if a firm does not intentionally collect data.
3. In general, the marketing literature conceptualizes value as consisting of both benefits and costs. The term "value" in this article refers only to benefits. This perspective is consistent with that of many authors in this area.
4. The practical use of such technology is still in its infancy, but early applications such as YourShow (which integrates Google Glass with presentation software), KitchMe (which provides cooking instruction on the Google Glass screen), and Evernote for smartwatches provide examples of how frontline employees can glean customer-specific information from mobile usage while serving the customer.
5. Ayres (2007, pp. 29-30) describes such empathy potential of big data value use at the point of service for Continental Airlines, which had a data-mining program in place that kept track of critical service experiences and informed the crew, citing CRM executive Kelly Cook as follows: "Recently, a flight attendant walked up to a customer flying from Dallas to Houston and said, 'What would you like to drink? And, oh, by the way, I am so sorry we lost your bag yesterday coming from Chicago.' The customer flipped."

References

Argyris, Chris (1985), *Strategy, Change and Defensive Routines*. Southport, England: Pitman Publishing Strategy.

Ayres, Ian (2007), *Super Crunchers: Why Thinking-by-Numbers Is the New Way to Be Smart*. New York, NY: Bantam.

Azzarello, Domenico, Frederic Debruyne, and Ludovica Mottura (2012), "The Chemistry of Enthusiasm," Bain Brief, Bain and Company, (accessed July 10, 2015), [available at www.bain.com].

Babakus, Emin, Ugur Yavas, Osman M. Karatepe, and Turgay Avci (2003), "The Effect of Management Commitment to Service Quality on Employees' Affective and Performance Outcomes," *Journal of the Academy of Marketing Science*, 31 (3), 272-286.

Becker, Gary S. (1976), *The Economic Approach to Human Behavior*. Chicago, IL: University of Chicago Press.

Bitner, Mary Jo (1992), "Servicescapes: The Impact of Physical Surroundings on Customers and Employees," *Journal of Marketing*, 56 (April), 57-71.

Bock, Gee-Woo, Robert W. Zmud, Young-Gul Kim, and Jae-Nam Lee (2005), "Behavioral Intention Formation in Knowledge Sharing: Examining the Roles of Extrinsic Motivators, Social-Psychological Forces, and Organizational Climate," *MIS Quarterly*, 29 (1), 87-111.

Boisot, Max and Agustí Canals (2004), "Data, Information and Knowledge: Have We Got It Right?" *Journal of Evolutionary Economics*, 14 (1), 43-67.

Brohman, M. Kathryn, Richard T. Watson, Gabrielle Picccoli, and A. Parasuraman (2003), "Data Completeness: A Key to Effective Net-Based Customer Service Systems," *Communications of the ACM*, 46 (6), 47-51.

Brown, Brad, David Court, and Tim McGuire (2014), "Views from the Front Line of the Data-Analytics Revolution," *McKinsey Quarterly*, (March), (accessed November 4, 2016), [available at http://www.mckinsey.com/business-functions/business-technology/our-insights/views-from-the-front-lines-of-the-data-analytics-revolution].

Brown, Brad, David Court, and Paul Willmott (2013), "Can Your C-Suite Handle Big Data?" *Harvard Business Review*, (accessed July 15, 2016), [available at https://hbr.org/2013/10/can-your-c-suite-handle-big-data/].

Brynjolfsson, Erik, Jeffrey Hu Yu, and Mohammad S. Rahman (2013), "Competing in the Age of Omnichannel Retailing," *MIT Sloan Management Review*, 54 (4), 23-29.

Brynjolfsson, Erik, Lorin Hitt, and Heekyung Kim (2011), "Strength in Numbers: How Does Data-Driven Decision making Affect Firm Performance?", (accessed April 22, 2011), [available at https://ssrn.com/abstract=1819486 or http://dx.doi.org/10.2139/ssrn.1819486]

Camisón, César and Beatriz Forés (2010), "Knowledge Absorptive Capacity: New Insights for Its Conceptualization and Measurement," *Journal of Business Research*, 63 (7), 707-715.

Capgemini Consulting (2015), "Cracking the Data Conundrum: How Successful Companies Make Big Data Operational," (Jan. 14, 2015), (accessed September 23, 2016), [available at https://www.capgemini-consulting.com/cracking-the-data-conundrum]

Carden, Art (2011), "Retail Innovations in American Economic History: The Rise of Mass-Market Merchandisers," Working Paper Number 78, Independent Institute, Oakland, CA.

Cohen, Wesley M. and Daniel A. Levinthal (1990), "Absorptive Capacity: A New Perspective on Learning and Innovation," *Administrative Science Quarterly*, 35 (1), 128-152.

Court, David (2015), "Getting Big Impact from Big Data," McKinsey Quarterly, January, (accessed September 23, 2016), [available at http://www.mckinsey.com/business-functions/business-technology/our-insights/getting-big-impact-from-big-data].

Crossan, Mary M., Henry W. Lane, and Roderick E. White (1999), "An Organizational Learning Framework: From Intuition to Institution," *Academy of Management Review*, 24 (3), 522-537.

Davenport, Thomas H. (2014). *Big Data @ Work*. Boston, MA: Harvard Business Review Press

De Dreu, Carsten K.W., and Aukja Nauta (2009), "Self-Interest and Other-Orientation in Organizational Behavior: Implications for Job Performance, Prosocial Behavior, and Personal Initiative," *Journal of Applied Psychology*, 94 (4), 913-926.

Deighton, John and Peter A. Johnson (2013), "The Value of Data: Consequences for Insight, Innovation and Efficiency in the US Economy," *Data-Driven Marketing Institute*, 14, 1-105.

Delgado, Rick (2015), "Improving the Accuracy of Big Data Analysis," (accessed March 16, 2015), [available at http://dataconomy.com/improving-the-accuracy-of-big-data-analysis-2/].

Dwoskin, Elisabeth and Evelyn M. Rusli (2015), "The Technology that Unmasks Your Hidden Emotions," *The Wall Street Journal*, 265 (23), B1-B8.

Elliot, Andrew J. and Judith M. Harackiewicz (1996), "Approach and Avoidance Achievement Goals and Intrinsic Motivation: A Mediational Analysis," *Journal of Personality and Social Psychology*, 70 (3), 461-475.

Engen, Marit and Peter Magnusson (2015), "Exploring the Role of Front-Line Employees as Innovators," *Service Industries Journal*, 35 (6), 303-324.

Feit, Eleanor Mcdonnell, Pengyuan Wang, Eric T. Bradlow, and Peter S. Fader (2013), "Fusing Aggregate and Disaggregate Data with an Application to Multiplatform Media Consumption," *Journal of Marketing Research*, 50 (3), 348-364.

Gartner (2015), "Gartner Survey Shows More Than 75 Percent of Companies Are Investing or Planning to Invest in Big Data in the Next Two Years," Gartner Newsroom, (September 16, 2015), (accessed September 22, 2016), [available at http://www.gartner.com/newsroom/id/3130817]

Germann, Frank, Gary L. Lilien, and Arvind Rangaswamy (2013), "Performance Implications of Deploying Marketing Analytics," *International Journal of Research in Marketing*, 30 (2), 114-128.

Harrysson, Martin, Estelle Metayer, and Hugo Sarrazin (2012), "How 'Social Intelligence' Can Guide Decisions," *McKinsey Quarterly*, (November), (accessed July 5, 2016), [available at http://www.mckinsey.com/industries/high-tech/our-insights/how-social-intelligence-can-guide-decisions].

Hennig-Thurau, Thorsten, Markus Groth, Michael Paul, and Dwayne D. Gremler (2006), "Are All Smiles Created Equal? How Emotional Contagion and Emotional Labor Affect Service Relationships," *Journal of Marketing*, 70 (July), 58-73.

Hennig-Thurau, Thorsten, Kevin P. Gwinner, and Dwayne D. Gremler (2003), "Understanding Relationship Marketing Outcomes: An Integration of Relational Benefits and Relationship Quality," *Journal of Service Research*, 4 (3), 230-247.

IBM (2013), "Analytics: The Real-World Use of Big Data in Financial Services," Executive Report, IBM Institute for Business Value and Saïd Business School, University of Oxford.

Jayachandran, Satish, Subhash Sharma, Peter Kaufman, and Pushkala Raman (2005), "The Role of Relational Information Processes and Technology Use in Customer Relationship Management," *Journal of Marketing*, 69 (4), 177-192.

King, Rachael (2014), "AT&T Uses Big Data to Improve Customer Experience," *Wall Street Journal*, (accessed July 10, 2016), [available at http://blogs.wsj.com/cio/2014/06/03/att-uses-big-data-to-improve-customer-experience/].

Lane, Peter J., Balaji R. Koka, and Seemantini Pathak (2006), "The Reification of Absorptive Capacity: A Critical Review and Rejuvenation of the Construct," *Academy of Management Review*, 31 (4), 833-863.

LeBon, Joel and Dwight Merunka (2006), "The Impact of Individual and Managerial Factors on Salespeople's Contribution to Marketing Intelligence Activities," *International Journal of Research in Marketing*, 23 (4), 395-408.

Lewin, Arie Y., Silvia Massini, and Carine Peeters (2011), "Microfoundation of Internal and External Absorptive Capacity Routines," *Organization Science*, 22 (1), 81-98.

Liebowitz, Jay (2013), *Big Data and Business Analytics*. Boca Raton, FL: CRC Press.

Macdonald, Emma K. and Mark D. Uncles (2007), "Customer Savvy: Conceptualisation and Measurement," *Journal of Marketing Management*, 23 (5/6), 497-517.

Manyika, James, Michael Chui, Brad Brown, Jacques Bughin, Richard Dobbs, Charles Roxburgh, and Angela Hung Byers (2011), "Big Data: The Next Frontier for Innovation, Competition, and Productivity," *McKinsey Global Institute*, (May), 1-143.

Marr, Bernard (2016), "Why Investments in Big Data Are Not Paying Off," *Forbes*, (accessed July 10, 2016), [available at http://www.forbes.com/sites/bernardmarr/2016/06/27/why-investments-in-big-data-and-analytics-are-not-yet-paying-off/#1b3cd64680a2].

Marr, Bernard (2015), "Big Data: A Game Changer in the Retail Sector," *Forbes*, (accessed March 22, 2016), [available at http://www.forbes.com/sites/bernardmarr/2015/11/10/big-data-a-game-changer-in-the-retail-sector/#638fa108678a].

McAfee, Andrew and Erik Brynjolfsson (2012), "Big Data: The Management Revolution," *Harvard Business Review*, 90 (10), 61-67.

McWhirter, Darien A. and Jon D. Bible (1992). *Privacy as a Constitutional Right*. New York: Quorum Books.

Meuter, Matthew L., Mary Jo Bitner, Amy L. Ostrom, and Stephen W. Brown (2005), "Choosing Among Alternative Service Delivery Modes: An Investigation of Customer Trial of Self-Service Technologies," *Journal of Marketing*, 69 (2), 61-83.

Montgomery, Alan and Kannan Srinivasan (2002), "Learning about Customers without Asking," in *The Power of One: Leverage Value from Personalization Technologies*, Nirmal Pal and Arvind Rangaswamy, eds. University Park, PA: eBRC Press, Penn State University, 122-143.

Moorman, Christine, Gerald Zaltman, and Rohit Deshpandé (1992), "Relationships between Providers and Users of Market Research: The Dynamics of Trust within and between Organizations," *Journal of Marketing Research*, 29 (3), 314-328.

Nonaka, Ikujiro (1994), "A Dynamic Theory of Organizational Knowledge Creation," *Organization Science*, 5 (1), 14-37.

Oaks, Jessica (2015), "4 Big Companies Using Big Data Successfully," (accessed on April 20, 2016), [available at http://www.smartdatacollective.com/jessoaks11/330428/4-big-companies-using-big-data-successfully].

Parasuraman, A., Valarie A. Zeithaml, and Leonard L. Berry (1988), "SERVQUAL: A Multiple-Item Scale for Measuring Customer Perceptions of Service Quality," *Journal of Retailing*, 64 (1), 12-40.

Ray, Gautam, Dazhong Wu, and Prabhudev Konana (2009), "Competitive Environment and the Relationship between IT and Vertical Integration," *Information Systems Research*, 20 (4), 585-603.

Rizzatti, Lauro (2014), "Big Data Requires Massive Amounts of Verification," (accessed September 23, 2016), [available at http://embedded-computing.com/guest-blogs/big-data-requires-massive-amounts-of-verification/].

Rust, Roland T. and Katherine N. Lemon (2001), "E-Service and the Customer," *International Journal of Electronic Commerce*, 5 (3), 85-101.

Saboo, Alok R., V. Kumar, and Insu Park (2016), "Using Big Data to Model Time-Varying Effects for Market Resource (Re)Allocation," *Management Information Systems Quarterly*, forthcoming.

Santos-Vijande, María Leticia, José Ángel López-Sánchez, and John Rudd (2016), "Frontline Employees' Collaboration in Industrial Service Innovation: Routes of Co-Creation's Effects on New Service Performance," *Journal of the Academy of Marketing Science*, 44 (3), 350-375.

Sathi, Arvind (2014), *Engaging Customers Using Big Data: How Marketing Analytics Are Transforming Businesses*. New York: Palgrave MacMillan.

Smith, Cooper (2014), "Most Retailers Plan to Soon Be Able to Identify Customers When They Walk into Their Stores," *Business Insider*, (June 16), (accessed August 20, 2015), [available at http://www.businessinsider.com/in-five-years-three-fourths-of-retailers-plan-to-be-able-to-identify-store-customers-2014-6?IR=T].

Thau, Barbara (2014), "How Big Data Helps Stores Like Macy's and Kohl's Track You Like Never Before," *Forbes*, (accessed March 22, 2016), [available at http://www.forbes.com/sites/barbarathau/2014/01/24/why-the-smart-use-of-big-data-will-transform-the-retail-industry/#57373c322cd4].

Van den Bosch, Frans A.J., Henk W. Volberda, and Michiel de Boer (1999), "Coevolution of Firm Absorptive Capacity and Knowledge Environment: Organizational Forms and Combinative Capabilities," *Organization Science*, 10 (5), 551-568.

Varon, Elana (2013), "How UPS Trains Front Line Employees to Use Predictive Analytics," (accessed July 15, 2015), [available at http://data-informed.com/how-ups-trains-front-line-workers-to-use-predictive-analytics/].

Venkatesh, Viswanath, James Y.L. Thong, and Xin Xu (2012), "Customer Acceptance and Use of Information Technology: Extending the Unified Theory of Acceptance and Use of Technology," *MIS Quarterly*, 36 (1), 157-178.

Villars, Richard L., Carl W. Olofson, and Matthew Eastwood (2011), "Big Data: What It Is and Why You Should Care," White Paper, International Data Corporation, Framingham, MA.

Wagner, Richard K., Harish Sujan, Mita Sujan, Carol A. Rashotte, and Robert J. Sternberg (1999), "Tacit Knowledge in Sales," in *Tacit Knowledge in Professional Practice: Researcher and Practitioner Perspectives*, Robert J. Steenberg and Joseph A. Horvath, eds. New York: Routledge, 155-183.

Wahba, Phil (2016), "The Man Who's Re-(Re-Re) Inventing J.C. Penney," *Fortune*, 173 (3), 76-86.

Walker, Michael (2012), "Data Veracity," (accessed March 15, 2016), [available at http://www.datasciencecentral.com/profiles/blogs/data-veracity].

Wamba, Samuel Fosso, Shahriar Akter, Andrew Edwards, Geofrrey Chopin, and Danis Gnanzou (2015), "How 'Big Data' Can Make Big Impact: Findings from a Systematic Review and a Longitudinal Case Study," *International Journal of Production Economics*, 165 (July), 234-246.

Wikibon (2012), "A Comprehensive List of Big Data Statistics," (accessed July 28, 2016), [available at wikibon.org/blog/big-data-statistics].

Wong, Maggie Hiufu (2015), "Japan's Robot Hotel Opens Its (Automatic) Doors," CNN, (accessed August 20, 2015), [available at http://edition.cnn.com/2015/07/17/travel/japan-hotel-robot-opens/].

Ye, Jun, Detelina Marinova, and Jagdip Singh (2012), "Bottom-Up Learning in Marketing Frontlines: Conceptualization, Processes, and Consequences," *Journal of the Academy of Marketing Science*, 40 (6), 821-844.

Zahra, Shaker A. and Gerard George (2002), "Absorptive Capacity: A Review, Reconceptualization, and Extension," *Academy of Management Review*, 27 (2), 185-203.

Zeithaml, Valarie A., Leonard L. Berry, and A. Parasuraman (1996), "The Behavioral Consequences of Service Quality," *Journal of Marketing*, 60 (April), 31-46.

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